Migrant Entrepreneurship, High-Growth Firms and Cities[*]

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January 9, 2026

Abstract: This paper examines migrants' role in founding high-growth firms and the urban nature of high-growth entrepreneurship. Although high-growth firms represent a small share of businesses in OECD countries, they disproportionately drive national economic activity. Using novel founder- and firm-level data on over 17,000 UK companies and 24,000 founders, we establish four new facts. First, migrant entrepreneurs are substantially over-represented among founders of high-growth and high-growth-potential firms, relative to the migrant population overall. Second, migrant founders differ significantly from UK-born founders in levels and types of human capital and labour market experience. Third, high-growth firms are highly urbanised, and those with a migrant founder or co-founder display a distinctive urban geography that does not reflect migrants' underlying spatial distribution. Fourth, firms with mixed native-migrant founding teams follow distinct growth paths, and develop more novel products and services, than those with all-UK teams. Future versions will explore how founder, firm, and area characteristics interact to explain these relationships.

JEL classification: J61, L26, O31, R10, R12
Keywords: entrepreneurship, immigration, cities, high-growth firms

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1 Introduction

This paper sits at the intersection of three topics: cities, migrant entrepreneurship, and high-growth firms. High-growth firms make a disproportionate contribution to national employment, innovation, and productivity growth. Although they account for only a small share of all firms—around six percent in the UK (NESTA, 2010)—these companies are central to debates about long-run economic growth and the design of public policies. More broadly, entrepreneurship itself is widely viewed as a driver of long-term economic growth (Schumpeter, 1962), though there remains an ongoing debate about the strength and nature of entrepreneurship–growth linkages, and the appropriate role for public policy in supporting entrepreneurial activity (Audretsch, 2007).

A large literature documents the outsize role of migrants in entrepreneurship: in self-employment and as entrepreneurs (defined as founders of companies that employ others); as founders of high-growth firms; and third, as key actors in high-technology clusters such as Silicon Valley. See Chodavadia et al. (2024) for a review. There is less agreement on the mechanisms underlying these patterns. One strand of literature views entrepreneurial success as largely stochastic, shaped by experimentation and random shocks (Kerr et al., 2014). Another emphasises the role of observable founder characteristics, including age, ambition, family background, and human or financial capital (Guzman and Stern, 2015, 2020). This logic suggests a first channel: if migrants disproportionately possess particular endowments, the firms they found may achieve outsize success (Azoulay et al., 2022). Migrants are positively selected on human capital (Hunt and Gauthier-Loiselle, 2010; Lee et al., 2025), and migrant and non-UK-national entrepreneurs may further select on risk tolerance and entrepreneurial attributes.

Second, minority ethnic entrepreneurs may also benefit from co-ethnic group membership, networks, and information spillovers: a extensive literature in economic sociology and entrepreneurship qualitatively documents these processes (Kerr, 2010; Kerr and Mandorff, 2023). Third, classic work on high-technology clusters also emphasises the role of migrant founders in shaping regional innovation systems (Saxenian, 2006), a theme further developed in later syntheses of the technology cluster literature (e.g. Kerr and Robert-Nicoud (2020)). Spatial characteristics, particularly those associated with cities, may also shape entrepreneurial firm formation and subsequent performance (Chinitz, 1961; Glaeser and Kerr, 2009; Glaeser et al., 2010; Storper et al., 2015; Glaeser et al., 2015; Faggio et al., 2017; Duranton and Puga, 2023). Cities offer agglomeration economies through matching, sharing, and learning mechanisms that influence entrepreneurship, innovation, and productivity (Duranton and Puga, 2023). More complex activities tend to sort into urban areas as they benefit from localised learning and thick labour markets, generating self-reinforcing spatial patterns (Davis and Dingel, 2019; Balland et al., 2020; Kemeny and Storper, 2020; Koster and Ozgen, 2021). If diversity operates as a production complementarity, these agglomeration forces may amplify firm-level effects. Urban demography may also matter directly, if city-level diversity expands the pool of ideas or improves labour market matching. In addition, a large literature shows that urban ethnic

enclaves influence minorities' economic outcomes (Edin et al., 2003; Wahba and Zenou, 2012; Marinoni, 2023; Marinoni and Choudhury, 2024). These mechanisms may be especially relevant for startups and young firms, for which large cities can act as "nurseries" (Duranton and Puga, 2001).

Against these narratives, other work highlights the role of constraints and exclusion. Limited access to mainstream labour markets may push some individuals into entrepreneurship (Kloosterman and Rath, 2003; Jones et al., 2018), while discrimination may constrain firm survival and growth (Fairlie et al., 2022). Recent work is more skeptical of claims that migrants are inherently more entrepreneurial or more successful, once individual characteristics such as age, gender, and human capital are taken into account (Manning, 2025). In the UK context in particular, migrants start businesses at higher rates than natives, especially in cities, where migrants are more likely to live, but these firms are also more likely to fail. Overall, this literature suggests that migrant entrepreneurship may reflect necessity rather than choice in many settings.

1.1 Research questions

This paper focuses explicitly on choice entrepreneurship, examining a very rich subsample of high-growth and high-growth-potential companies and their founders in the UK between 2000 and 2020. The firms in our data are highly selected - they represent under 5% of all UK firms - but they are precisely the segment most relevant for understanding entrepreneurship-led growth. Given their economic importance, it is critical to understand how such firms are formed and the extent to which founder characteristics, founding team composition, and area characteristics can help explain their outcomes.

Against this backdrop, we study the characteristics and geography of migrant entrepreneurs and mixed founding teams among high-growth and high-growth-potential firms in the UK. In this version of the paper we ask four linked questions:

1. How do migrant founders—entrepreneurs—differ from UK-born founders in terms of observable characteristics, especially age, gender, human capital, education and career histories?

2. How are high-growth firms and their founders distributed across space, and how urbanised are these patterns?

3. How does founding team composition vary across high-growth firms founded by UK-born entrepreneurs, migrant entrepreneurs, and mixed teams combining foreign-born and native founders?

4. Are high-growth firms founded by migrant entrepreneurs or mixed teams more successful than those founded by UK-born entrepreneurs, across a range of outcomes?

In the next version of the paper we will explore the interactions between founder, firm and area characteristics in detail.

The UK context is of particular interest. While there is extensive evidence on migrant entrepreneurship in the US, much less is known about the composition and performance of migrant-founded high-growth firms in the UK, despite its openness to skilled migration and the strong spatial concentration of entrepreneurial and innovative activity, especially in London and other large cities. Moreover, most existing work in the UK focuses either on individual founders or on firms as homogeneous units, paying less attention to the demographic composition of founding teams and the potential for complementarities across founders of different backgrounds.

Our analysis focuses on a highly selected but economically important sample: firms identified as high-growth or high-growth-potential based on observable lifecycle "triggers" such as academic spinouts, firms receiving external finance, or firms experiencing rapid employment or revenue growth. While these firms represent a small fraction of the total firm population, they account for a large share of job creation and innovation, making them central to policy-relevant questions about entrepreneurship and growth.

1.2 Findings and roadmap

We first document that migrant entrepreneurs are substantially over-represented among founders of high-growth and high-growth-potential firms in the UK. The share of migrant founders in our data is at least double their share in the working-age population, even though our measure of migrant status is conservative. Entrepreneurs are not a random draw from the workforce, so we also compare migrant and UK-born founders directly. We show that migrant and UK-born founders are similar along several dimensions such as age, gender, and years of work experience, but differ markedly in others. Migrant founders tend to have higher levels of formal education, are more likely to hold STEM or economics qualifications, have worked in a larger number of jobs, and are more likely to have technical or scientific career backgrounds. Many of these differences hold when we control for other observables, firm and location characteristics.

Next we document the geographies of these high-growth companies and their founders (who may or may not be co-located with businesses). We show that the high-growth and high-growth potential companies in our data have a strongly urban footprint, with disproportionate shares in London, conurbations, and university cities - notably Oxbridge. Firms with a migrant founder or co-founder have an even stronger urban footprint, and are much more clustered in London and Oxbridge. When we switch focus to founder location, we find that migrant founders largely follow these spatial patterns, although we also find a significant share of migrant founders are now based outside the UK.

Finally, focusing on co-founded firms, we show that founding team composition is strongly correlated with firm performance. Firms founded by all-UK teams, all-migrant teams, and

mixed teams follow systematically different growth paths across multiple dimensions, including accruing revenue, adding headcount, accessing external finance, and exit events. Building measures of product distinctiveness from firm text, we also find that mixed founding teams - combining migrant and UK-born founders - develop more original products and services than all-UK founding teams. While our analysis at this stage is descriptive rather than causal, these patterns are consistent with the presence of founder-level synergies - arising from cognitive or functional diversity within teams - that influence firm performance.

Given the highly urbanised footprints of these firms, especially those with migrant founders and co-founders, in the next iteration of the paper we will explore urban/spatial factors that may influence firm outcomes, and how these interact with individual and firm-level characteristics.

1.3   Related literature

This paper contributes to several strands of the literature. First, it adds to work on migrant entrepreneurship by providing new evidence from the UK on the characteristics and performance of migrant-founded high-growth firms, using linked founder–firm data with unusually rich information on education and career histories. Second, it contributes to the growing literature on entrepreneurial teams by explicitly distinguishing between all-native, all-migrant, and mixed founding teams, and by documenting systematic differences in outcomes across these groups. Third, we contribute to the geography of entrepreneurship literature by showing how migrant-founded and mixed-team firms exhibit distinct spatial patterns of co-location, particularly in large and diverse cities such as London. Finally, methodologically, we introduce novel measures of product and service distinctiveness derived from firm-level text data, allowing us to study how founding team composition relates not only to growth and survival, but also to the originality of firms' market offerings.

The closest paper to this one is Jin et al. (2025) who look at migrant entrepreneurship and founding team synergies in the US using broadly similar data. Their paper does not include any spatial analysis; and given the distinctive role of skilled migrant entrepreneurs in the US innovation system, their findings may not generalise outside the US.

2   Data

We develop rich information on high-growth companies and their founders, via two main data sources. Our primary firm-level data come from Beauhurst, a commercial provider that tracks high-growth and high-growth-potential companies in the United Kingdom.[1] We link Beauhurst founders to individual profiles in Diffbot, a very large commercial knowledge graph database constructed from the public web.[2] Below we provide more details of these data:

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[1] See www.beauhurst.com for more detail.
[2] See www.diffbot.com for more detail.

1. **Beauhurst** is a dataset of 'high-growth' or 'high-growth-potential' UK companies, including company level characteristics (age, industry, headcount, etc), geolocated trading addresses, detailed rich-text descriptions and financial performance measures (external finance, revenues). Companies are selected on the basis of one or more lifecycle events, which Beauhurst treats as 'growth signals'. Some of these signals are early-stage (being an academic spin-out, attending an accelerator programme or receiving an innovation grant) and others are later stage (receiving angel or VC finance, high-revenue growth or employment growth episodes). Beauhurst start with the UK's open companies registry, Companies House, and enrich this through multiple other sources. Our current dataset covers 44,100 companies, of which 33,400 companies are founded 2000-2020 inclusive. The dataset also covers 257.9k 'key individuals', including firm founders, company officers, other top employees and investors/shareholders. For these individuals we have names, ages, gender, nationalities, and information on previous founder / employee / board roles. Beauhurst identifies 33.5k of these individuals as founders, based on their job titles.

2. **Diffbot** is a global knowledge graph database built from the public internet, using feature extraction and supervised learning (Mesquita et al., 2019). Graph databases link entities (such as firms, founders, workers and places) through meaningful relationships (such as founding activity, employment histories and trading addresses). As of January 2025, Diffbot's graph contained 231.3M individuals with employment histories globally, of which 10.6M were in the UK. For these individuals, who will include company founders, Diffbot profiles include names, age, gender and detailed education and career histories, including details of job spells, roles and work locations. Diffbot also contains granular 'skills' for individuals, based on profiles, and leveraging a validated typology of 32,000 skills. Importantly, Diffbot's graph includes Companies House information including company identifiers, as well as many other open company registers from around the world. Building on methods developed in Nathan et al. (2025), we use this feature to link organisations and people in Diffbot to companies and founders in Beauhurst. We detail our workflow below.

2.1 Defining founders

We define company founders as entrepreneurs - individuals who set up companies which then employ others. 'Founder' has no legal definition, however, and so identifying company founders in data is not straightforward. We identify 33,486 all-time company founders and co-founders in Beauhurst by searching on validated roles and job titles. This is a conservative approach which precisely identifies a set of self-identified entrepreneurs. However, not all companies in our data have 'founders' or 'co-founders' listed.[3] We drop these companies from our analysis,

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[3]For example, some entrepreneurs may not see themselves as 'founders', rather as 'someone who owns a business' (email exchange with Beauhurst, December 2025).

reducing our sample of companies to 23,944. An alternative approach involves identifying the first appointed director of a company, which identifies founding board members and typically produces much higher counts. We run tests showing this approach generates inflated founder counts.[4] Overall, we deem the significant reduction in company sample size acceptable given the correspondingly significant gain in precision.

2.2 Founder - company sample

Beauhurst person profiles contain only limited information on individuals. We first gapfill missing data by scraping Companies House for updated profile information on identified founders. We then search for founders on Diffbot and extract person profiles, providing us with much richer information. To do this:

1. We search for companies in Diffbot, then for matched companies we further search for founders.

2. We initially keep only matches where companies are matched by identifier or name and UK location, and where founders are matched by name.

3. A research assistant manually validated matches for a random sample of 100 founders.

4. We use an LLM-based workflow to adjudicate edge cases where founders are matched on first name or surname only, using contextual information to resolve matches/non-matches.[5]

We use cleaning routines detailed in Nathan et al. (2025) to build detailed Diffbot founder profiles, which we then match to Beauhurst founders and companies. Our final sample consists of Beauhurst companies founded in 2000 or later, which have identified founders, and whose founder/s are well-matched to Diffbot profiles. From our initial sample of 33,486 founders we match 31,767 to Diffbot profiles, and keep 26,379 matches, an overall match rate of 78.8%. Restricting to firms founded in 2000-2020 further reduces our sample to 24,060 founders. Correspondingly, our starting sample of 23,944 companies with identified founders reduces to 22,689 where founders are matched to Diffbot, 19,739 with well-matched founders, and to 17,040 companies founded between 2000 and 2020.

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[4]Companies may be running for some while, including with employees, before they formalise governance arrangements; many companies appoint whole boards at single time points; some individual directors sit on many boards. Taken together these issues imply inflated counts. Applying the first director definition to our data generates 122.5k 'founders', around four times as many as using the self-identified basis. Further, the median firm now has six 'founders' and the largest 'founding team' has 143 members. These numbers are too big to be credible.

[5]Two examples illustrate the issue. Example 1: Edward E Johnson in Beauhurst / Woody Johnson in Diffbot. Both listed as a director of ABC Import Export, a company based in London with CRN GB123456. Our algorithm matches on the company and the surname. We accept the match: Woody is a known diminutive of Edward, and other contextual information checks out. Example 2: Luke Antonidis in Beauhurst / Diana Antonidis in Diffbot. Both listed as a director of XYS Strategies, a consultancy based in Manchester with CRN GN654321. Our algorithm matches on the company and the surname. We reject the match: Luke and Diana are very unlikely to be the same person; this is likely a family firm.

2.3 Defining migrant status

A fundamental constraint in migrant entrepreneurship research is that rich data on company founders often does not observe country of birth. Neither Beauhurst or Diffbot directly observes country of origin. Beauhurst - and the UK companies registry - contains nationality information, which is often used as a proxy for migrant status (Acosta and Marinoni, 2025). However, nationality is both endogenous and not perfectly overlapping with migrant status – for example, in the UK in 2021, 43% of migrants held UK passports (Migration-Observatory, 2023). Using nationality as a noisy proxy for migrant status could simply lead to attenuation bias. However, the 2016 EU referendum result will also have led many EU migrants to apply for UK nationality, potentially introducing more structural bias into the measure.

Instead, and in line with Lee and Glennon (2023), Jin et al. (2025) and other recent studies, we proxy for migrant status by using founders' country of education, focusing on the lowest observed level of education in Diffbot profiles (typically undergraduate university education). UK universities attract more foreign students than UK students study abroad - 2022/3, 26% of all UK students were born abroad (HESA, 2024) - so this proxy is likely to give a lower bound on migrant founders. We validate this approach using an online survey of UCL staff, finding nearly 99% correct attribution, as well as the predicted lower bound on true migrant status. Note that over 20% of founders do not have any education information in their Diffbot profiles. We assume this is noise.

2.4 Outcome measures

We explore two types of company outcomes: business performance metrics, drawing on company accounts, and company 'distinctiveness', which we build from company text data. We view the latter as a proxy for innovation. We also show that distinctiveness measures are correlated with other performance metrics in interpretable ways.

Beauhurst contains an array of business performance data. Firms in Beauhurst have a range of potential growth paths, from sales and revenue-maximisation to VC-led scaling (building up user base / market share with or without revenue). To reflect this breadth, in this version of the paper we construct simple dummy variables covering whether the firm has any revenue post-incorporation, whether the firm has any employees, whether the firm has any external finance, whether the firm has been acquired, or whether it has exited (e.g. through an IPO). In future versions of the paper we will use the full panel structure of the data to look at levels and changes in these outcomes.

We build measures of distinctiveness based on companies' descriptions of their products and services. We follow a growing literature using natural language processing to explore company strategy (Draca et al., 2023; Guzman and Li, 2022; Hoberg and Phillips, 2016). Adapting the workflow from Draca et al, we clean the text from the Beauhurst 'description' field, build a TF-IDF matrix of the resulting text, and compute cosine similarities between each pair of

companies in our data. We define a data-driven global similarity threshold, which we set as the 95th percentile of all pairwise similarities (cosine similarity is scaled -1 to 1, and our threshold is 0.064).

For each firm, we then construct a) the count of peers, defined as firms above the similarity threshold; and b) a dummy for singleton status, defined as having no peers. We set these both globally (across all companies) and more narrowly (for blocs of companies founded in the same year, and in the same SIC 3-digit industry). We also measure c) company 'originality', defined as (1 - maximum similarity of any company founded in earlier years), and d) cohort 'trendiness', defined as a company's mean similarity with all others founded in the same year.

3 Descriptives

3.1 Founders

Founder demographics. Table 1 summarises core demographic characteristics of the founders. Consistent with the wider literature on successful entrepreneurs, the average founder age for these high-growth companies is over 47. Over 80% of founders are male. In both cases, there is minimal raw difference between migrant and UK-born founders. We estimate that 26.5% of founders are migrants, measured by our country of education proxy. This is almost double the share of migrants in the UK working-age population and as explained above, is likely to be a lower bound. 30.7% of founders are non-UK nationals: however we estimate over 20% of these are UK-born, highlighting the challenges in using nationality as a proxy for migrant status.

Founder characteristics. Figure 1 summarises mean characteristics for migrants and UK-born founders. As well as similar age, gender profiles, migrant founders have similar years of labour market experience to native founders. However, they differ on levels and types of qualifications, and types of professional experience. T-tests show that (virtually) all of these raw migrant-native differences are statistically significant: see Appendix Table A1.

As Manning (2025) points out, such bivariate differences have limited explanatory power if migrants and natives structurally differ on observables (e.g. age distribution). In further tests we therefore run regressions to test migrant-native differences on each observable characteristic, while controlling for all other observables, for company characteristics, and firm cohort and detailed location dummies. Results, available on request, show that migrant founders are significantly older than UK-born founders; more likely to be non-UK nationals; speak more languages; are more likely to have an economics degree; are more likely to have post-graduate qualifications and/or a PHD; and are less likely to be serial founders or based in London.

Founder location. Table 2 shows founders' current location, derived using Diffbot profile information. Note that this is missing for around 50% of founders, so this part of the results should be used with caution, although it is quite consistent with company location analysis

Table 1: Founder characteristics by migrant status

	All founders	UK-born	Migrants
Founder age	47.66	47.74	46.29
	(11.47)	(11.38)	(10.59)
Founder age (Beauhurst)	45.63	44.25	42.83
	(11.77)	(11.29)	(10.65)
Female founder	0.18	0.18	0.20
	(0.39)	(0.39)	(0.40)
Female founder (Beauhurst)	0.18	0.19	0.19
	(0.38)	(0.39)	(0.39)
Non-UK national	0.31	0.21	0.65
	(0.46)	(0.41)	(0.48)
Dual nationality incl. UK	0.01	0.00	0.02
	(0.08)	(0.07)	(0.12)
Migrant founder	0.27	–	–
	(0.44)		

Note: Means with standard deviations in parentheses. Source: Beauhurst, Diffbot. Founders of companies founded 2000–2020.
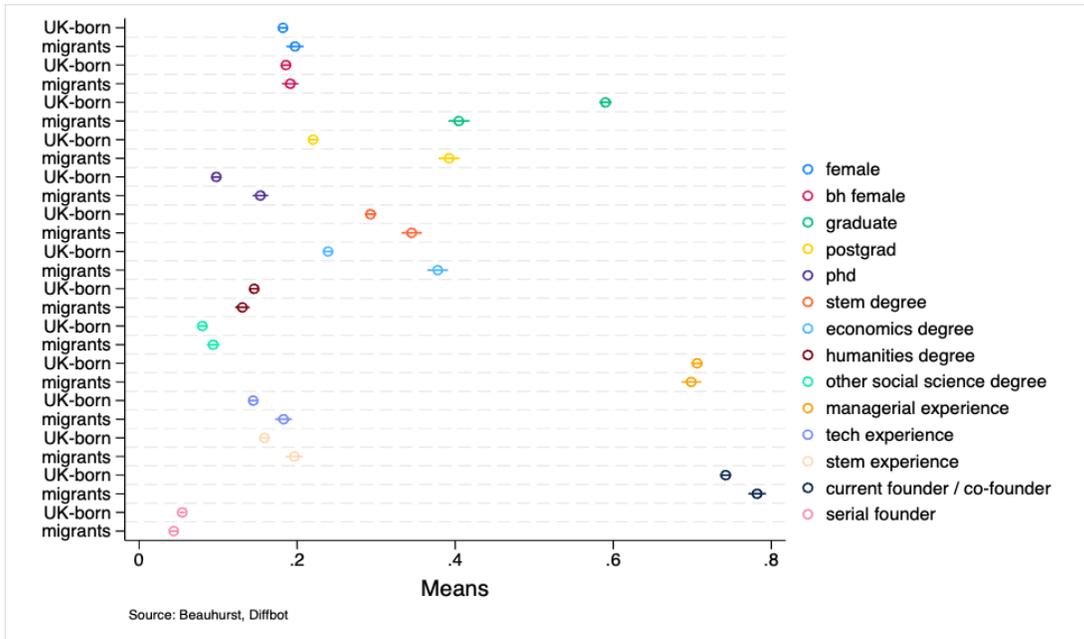
Note: Source: Beauhurst, Diffbot. Founders of companies founded 2000-2020 inclusive.

Figure 1: Founder characteristics by origin

Table 2: Founders' current location

| | all founders | | | Migrant founders | |
count	share	city	count	share	city
4515	16.92	London	1154	22.30	London
248	0.93	Edinburgh	64	1.24	Cambridge
243	0.91	Manchester	46	0.89	Edinburgh
222	0.83	Bristol	40	0.77	Oxford
210	0.79	Cambridge	28	0.54	Manchester
166	0.62	Glasgow	24	0.46	New York City
149	0.56	Leeds	22	0.43	Glasgow
138	0.52	Birmingham	20	0.39	Bristol
119	0.45	Oxford	20	0.39	Paris
111	0.42	Newcastle Upon Tyne	18	0.35	Birmingham
89	0.33	Cardiff	15	0.29	Milan
73	0.27	Hove	14	0.27	Sydney
57	0.21	Nottingham	12	0.23	Moscow
55	0.21	Bath	10	0.19	Munich
55	0.21	Aberdeen	10	0.19	Hove
54	0.20	Sheffield	10	0.19	Leeds
52	0.19	Liverpool	9	0.17	Rome
48	0.18	New York City	9	0.17	Dublin
48	0.18	Southampton	8	0.15	Melbourne

Source: Beauhurst, Diffbot. Founders of companies founded 2000-2020 inclusive. Area units are cities (em_city in Diffbot). Note: location info comes from Diffbot, and includes founders of UK companies who are now no longer in the UK.

which uses complete trading address information. Panel A shows all founders. Panel B shows migrant founders. Overall, founders are most likely located in London, big cities or university cities. Migrant founders have a somewhat different footprint, and are most concentrated in London, Oxbridge and Edinburgh. Notably, some migrant founders are not in the UK any more, with small groups in the US, France, Italy, Germany, Russia, Ireland and Australia. However, as we show below, while some migrant *founders* are now based outside the UK, their *companies* are more concentrated in London than the sample as a whole.

3.2 Companies

Founding team types. Table 3 decomposes the company sample by founding team types. About 44% of companies are co-founded; 56% are solo founded. Only 22% of solo-founded firms have a migrant founder. By contrast, around 40% of co-founded firms have at least one migrant founder; of these just under 23% have a mix of migrant and native founders, and just over 16% have all migrant founders.

Company location. Table 4 shows company trading location across Travel to Work Areas (TTWAs). TTWAs are self-contained commuting zones, which we use here as proxies for

Table 3: Founding team composition

	Share	N
At Least One Migrant Founder	29.7%	4,514
Sole-Founded Company	56.2%	8,534
Migrant Founder	22.5%	1,916
UK-born Founder	77.5%	6618
Co-Founded Company	43.8%	6,656
All Migrant Founders	16.1%	1,072
All UK-Born Founders	61.0%	4,058
Mixed Founding Team	22.9%	1,526
N	−	15,190

Source: Beauhurst, Diffbot. Founders of companies founded 2000-2020 inclusive.

local spatial economies. The table focuses on the top 20 TTWAs by company location counts. Panel A shows all companies. Panel B shows migrant-founded companies. Results are broadly consistent with the founder location analysis above. Overall, companies in Beauhurst are highly urbanised. Nearly 40% are in London, with other concentrations in contiguous 'mega-London' TTWAs such as Slough and Heathrow, Guildford and Aldershot, Luton and Reading. The next largest shares are in a mix of large conurbations (Manchester, Bristol, Birmingham, Leeds, Newcastle, Glasgow, Cardiff), and university cities (Cambridge, Edinburgh, Oxford, Aberdeen, Southampton). Migrant-founded companies show a much stronger London footprint, with nearly 60% in the capital, and rather higher shares in Cambridge and Oxford. Shares in other TTWAs are lower than for companies as a whole.

4 Analysis

Next we focus on co-founded firms, who comprise approximately 44 percent of our sample. We explore linkages between founding team demography and company outcomes. Specifically, we look at whether all-migrant founding teams and mixed founding teams have different outcomes to all-UK-born founding teams, controlling for other founder and company-level characteristics.

4.1 Scaling, growth and exit

Table 5 shows the results of linear probability models regressing company performance measures on founding team characteristics. Per Section 2.5, at this point we build dummy outcomes which take the value 1 if a firm has any employment, any revenue, has received any external finance, has exited or been acquired after incorporation. Future versions of the paper will build full panels and explore levels and growth in more detail. Each regression compares outcomes for migrant-only and mixed founding teams relative to all UK-born founding teams.

Table 4: Company Locations: Top 20 TTWAs

A. All Companies			B. Migrant-Founded Companies		
City	**N**	**Share**	**City**	**N**	**Share**
London	7,756	39.88	London	2,649	58.85
Manchester	710	3.65	Cambridge	157	3.49
Cambridge	524	2.69	Oxford	123	2.73
Edinburgh	503	2.59	Manchester	105	2.33
Bristol	485	2.49	Slough & Heathrow	96	2.13
Birmingham	457	2.35	Edinburgh	95	2.11
Oxford	390	2.01	Belfast	68	1.51
Slough & Heathrow	388	2.00	Bristol	63	1.40
Glasgow	342	1.76	Guildford & Aldershot	59	1.31
Cardiff	310	1.59	Birmingham	53	1.18
Leeds	292	1.50	Glasgow	51	1.13
Newcastle	283	1.46	Brighton	38	0.84
Belfast	278	1.43	Newcastle	36	0.80
Guildford & Aldershot	277	1.42	Milton Keynes	34	0.76
Brighton	251	1.29	Luton	33	0.73
Aberdeen	194	1.00	Southampton	31	0.69
Luton	182	0.94	Cardiff	28	0.62
Reading	165	0.85	Leeds	24	0.53
Southampton	159	0.82	Leamington Spa	23	0.51
Milton Keynes	158	0.81	Reading	22	0.49

Source: Beauhurst, Diffbot. Founders of companies founded 2000-2020 inclusive. Trading address data. Area units are Travel to Work Areas. Panel A sample conditional on companies where trading address is known. Panel B sample conditional on trading location and founder demography known.

Table 5: Founding Team Composition and Firm Outcomes

	Firm Performance Outcomes				
	(1)	(2)	(3)	(4)	(5)
	Employ	Revenue	Ext. Fin	Exit	Acq
Migrant-only	−0.020**	0.015*	0.081***	−0.001	−0.001
	(0.010)	(0.008)	(0.011)	(0.006)	(0.006)
Mixed	−0.013	0.029***	0.115***	0.012*	0.012*
	(0.009)	(0.009)	(0.011)	(0.006)	(0.006)
Test: Mixed = Migrant-only					
Difference	0.008	0.010	0.053	0.015	0.015
Std. error	(0.012)	(0.011)	(0.013)	(0.008)	(0.008)
p-value	0.510	0.351	0.000	0.052	0.052
Mean dep. var.	0.851	0.156	0.729	0.053	0.053
Observations	11,138	11,138	11,138	11,138	11,138
Adj. R^2	0.138	0.171	0.116	0.051	0.051

Notes: Linear probability models. Sample: UK companies founded 2000–2017 with at least two co-founders. Migrant-only = all founders are migrants. Mixed = at least one migrant and one UK-born founder. Omitted category = all-UK teams. Controls include founder gender, education, experience, managerial background, and team size. Fixed effects absorb 3-digit SIC industry × incorporation year interactions. Standard errors (in parentheses) clustered at industry-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Mixed migrant-native founding teams demonstrate an advantage in accessing external finance. Relative to all-UK teams, mixed teams are 11.5 percent more likely to receive external funding ($p < 0.01$), compared to 8.1 percent for migrant-only teams. Direct comparison shows mixed teams have a 5.3 percentage point funding advantage over migrant-only teams ($p < 0.001$). Mixed teams also show a marginally significant advantage in achieving exits through acquisition ($1.5pp, p = 0.052$). We find no significant differences across team types in employment generation or revenue realization; any mixed-team premium appears linked to investor access not operational performance.

4.2 Product distinctiveness

We first explore associations between product distinctiveness and the firm performance outcomes above. We focus on firms' originality compared to earlier-founded firms (a measure of novelty); and their similarity to other firms in the same cohort (a measure of 'trendiness'). These linkages are *a priori* ambiguous. Firms with more original products/services might attract more investor interest, gain higher market share and raise headcount. Conversely, to the extent investors and/or consumers exhibit herd behaviour, trendier firms might attract more interest from investors and/or greater interest from consumers.

Table 6 shows the results of linear probability models where we regress company performance outcomes on originality and trendiness metrics. The results strongly imply that more original firms attract more investor interest, but originality is linked to a lower probability of

employment, revenue or subsequent exit/acquisition. By contrast, 'trendy' firms are less likely to receive investment, but more likely to achieve revenue and/or employment and are more likely to be acquired.

Table 6: Validation: Product Distinctiveness Measures and Firm Outcomes

	Panel A: Originality (vs. Older Firms) as Predictor				
	(1)	(2)	(3)	(4)	(5)
	Employ	Revenue	Ext Fin	Exit	Acq
Originality	-0.055**	-0.134***	0.176***	-0.047***	-0.047***
	(0.024)	(0.023)	(0.030)	(0.015)	(0.015)
	Panel B: Trendiness (within Cohort) as Predictor				
	(6)	(7)	(8)	(9)	(10)
	Employ	Revenue	Ext Fin	Exit	Acq
Trendiness	0.569	1.869***	-3.936***	0.660***	0.660***
	(0.351)	(0.332)	(0.443)	(0.210)	(0.210)
Observations			31,852		
Adj. R^2	0.106	0.271	0.121	0.067	0.067

Notes: Linear probability models. Sample: UK companies founded 2000–2017 with at least two co-founders and available product description text. Originality measures distinctiveness relative to all previously founded companies (higher = more original). Trendiness measures similarity to firms founded in the same year (higher = more similar to cohort). Each column represents a separate regression. Controls include founder gender, education, experience, managerial background, and team size. Fixed effects absorb 3-digit SIC industry × incorporation year interactions. Standard errors (in parentheses) clustered at industry-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Next, we look at links between founding team demography and product distinctiveness. As above, for our initial exploration we run linear probability models regressing company distinctiveness measures on founding team characteristics. Each regression compares outcomes for migrant-only and mixed founding teams relative to all UK-born founding teams. Future versions of the paper will build full panels and explore levels and growth in more detail.

Table 7 gives results. We find that mixed migrant-native founding teams produce more distinctive products and services. Relative to all-UK teams, mixed teams create offerings that are 0.5 percentage points more original compared to all previously founded companies (p=0.041), while migrant-only teams show no significant difference. Neither team type differs on trendiness relative to same-year cohort peers.

5   Conclusion

In this preliminary paper, we use novel founder- and firm-level data on over 17,000 UK companies and 24,000 company founders to establish four new facts about migrant entrepreneurship, high-growth firms and cities. First, migrant entrepreneurs are substantially over-represented among founders of high-growth and high-growth-potential firms, relative to the migrant population overall. Second, migrant founders differ significantly from UK-born founders in levels

Table 7: Founding Team Composition and Product Distinctiveness

	Product Distinctiveness Measures	
	(1) Originality	(2) Trendiness
Migrant-only	0.001	−0.000
	(0.002)	(0.000)
Mixed	0.005**	0.000
	(0.003)	(0.000)
Test: Mixed = Migrant-only		
Difference	0.004	0.000
Std. error	(0.003)	(0.000)
p-value	0.129	0.622
Mean dep. var.	0.709	0.024
Observations	15,338	15,338
Adj. R^2	0.054	0.136

Notes: OLS regressions. Sample: UK companies founded 2000–2017 with at least two co-founders and available product description text. Originality measures distinctiveness of firm's products/services relative to all previously founded companies (higher = more original). Trendiness measures similarity to other firms founded in the same year (higher = more similar to cohort). Migrant-only = all founders are migrants. Mixed = at least one migrant and one UK-born founder. Omitted category = all-UK teams. Controls include founder gender, education, experience, managerial background, and team size. Fixed effects absorb 3-digit SIC industry × incorporation year interactions. Standard errors (in parentheses) clustered at industry-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and types of human capital and labour market experience. Third, high-growth firms are highly urbanised, and those with a migrant founder or co-founder display a distinctive urban geography that does not reflect migrants' underlying spatial distribution. Fourth, firms with mixed native-migrant founding teams follow distinct growth paths, and develop more novel products and services, than those with all-UK teams.

Overall, the analysis shows that founding team composition is systematically related to both firm outcomes and product characteristics. Mixed migrant–native teams stand out in their ability to access external finance and, to a lesser extent, achieve exits, suggesting complementarities in skills or networks that are valued by investors. These advantages do not translate into stronger short-run operational outcomes such as employment or revenue, indicating that the mixed-team premium operates primarily through capital markets rather than day-to-day performance. We also find that mixed teams produce more original products, while migrant-only teams do not differ significantly from all-UK teams in distinctiveness. Taken together, the results point to the importance of founder diversity in shaping innovation and investor perceptions, even when immediate firm growth outcomes remain similar across team types.

Future versions of the paper will explore how founder, firm, and area characteristics may interact to explain these relationships.

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A Appendix

Table A1: T-Tests

	Migrants vs All	Migrants vs Natives
founder age	***	***
founder age (beauhurst)	***	***
female founder	**	**
female founder (beauhurst)	**	.
non-uk national	***	***
dual nationality incl UK	***	***
highest qual college degree	***	***
highest qual postgraduate degree	***	***
highest qual PhD	***	***
has a degree in a STEM subject	***	***
has a degree in economics	***	***
has arts or humanities degree	.	**
has other social science degree	**	**
number of languages spoken	***	***
years of labour market experience	***	***
number of jobs in career history	***	***
has non-exec board experience	***	***
has experience in tech role	***	***
has experience in stem role	***	***
is currently a founder or co-founder	***	***
serial founder	*	**

Source: Beauhurst, Diffbot. *** = significant at 1%, ** = 5%, * = 10%.